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Optimization techniques to improve energy efficiency in power systems

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ABSTRACT

With the 2009/28/EC Directive, the European Union has to guarantee three objectives by 2020: 20% reduction in greenhouse gases emissions, 20% share of renewable energy and 20% improvement of energy efficiency. New technologies and policies applied to power systems can positively influence the overall energy efficiency. The dimensions and complexity of the power system discourage the use of exact optimization techniques and heuristic methods are an effective option to find a rapid, robust and good solution. This paper presents a review of articles with applications of heuristic methods to the transmission and distribution system with the aim of improving energy efficiency.

Contents

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1. Introduction

In the past years, electrical power systems have experienced changes in energy markets, energy technologies, energy policies and environmental awareness. New technologies can help managing voltage and power flow control, reactive compensation and power system security. Also, the number of renewable energy generators installed in power systems has increased noticeably and this means changes in generation and in the operation of the system. It is then clear that the system should be coordinated to match all the requirements so far mentioned: control adjustments, security, compensation and distributed generation. Power systems can be divided in three main sections: generation, transmission and distribution. This article presents a review of heuristic methods applications to the transmission and distribution (T&D) system. The amount of total losses in T&D can be reduced working in the above mentioned fields: energy technologies and energy policies. They both help increasing energy efficiency, a clear objective of the "'20–20–20"' strategy [1], but they also increase the complexity of the power system.

In the mathematical model of the T&D system, control objectives, operation requirements and overall objectives, including among others energy efficiency and economical return, set the basis for an optimization problem to be solved. An optimization problem has an objective function that has to be optimized and this function is subject to several constraints that represent the nature of the T&D system, as well as design and operational constraints. The solution of this problem can be found using different methods and usually the objective function and/or the constraints of the system present non-linearities that convert the optimization problem into a non-linear problem. Taking a further step, real power systems have dimensions that can make very difficult applying conventional computational techniques and that is the reason why heuristic techniques can be a good way to solve the optimization problem. Heuristic methods are not able to guarantee a global optimum as a conventional technique would do, but they provide good results in acceptable simulation times and they can be implemented to deal with the solution of a wide range of optimization problems, regardless their specific objective function or constraints.

The paper is structured as follows: Section 2 discusses the role of energy efficiency in modern power systems, how it is related to them and its importance when it comes to satisfy electrical policies. The most applied optimization techniques in power systems are presented in Section 3 along with a short explanation of how they are structured. Application examples of these techniques to some specific problems can be found in Sections 4 and 4.4 shows a detailed example of genetic algorithm applied to FACTS location. Section 5 draws the conclusions of the paper.

2. Energy efficiency: a policy and a technological issue

The European Union ratified the Kyoto Protocol [2] in May 2002 and committed to reduce emissions of greenhouse gases. Under the Kyoto Protocol industrialized countries agreed to reduce their emissions of greenhouse gases by 5.2% by the period 2008–2012 compared to the year 1990 (compared to the emissions levels expected by 2012 prior to the Protocol, this limitation represents a 29% cut). The Protocol encourages governments to cooperate with one another, improve energy efficiency, reform the energy and transportation sectors, promote renewable forms of energy, phase out inappropriate fiscal measures and market imperfections, limit methane emissions from waste management and energy systems, and protect forests and other carbon sinks. The target in Europe is an 8% reduction overall with a target for CO_2 emissions to fall by 20% by 2020. Of the six greenhouse gases listed by Kyoto, one of the most significant by volume of emissions is carbon dioxide (CO_2) and the 30% of its production is due to electricity and heat production as depicted in Fig. 1.

The Kyoto Protocol can be considered as the first step towards the mitigation of climate change effects. In 2007, the European

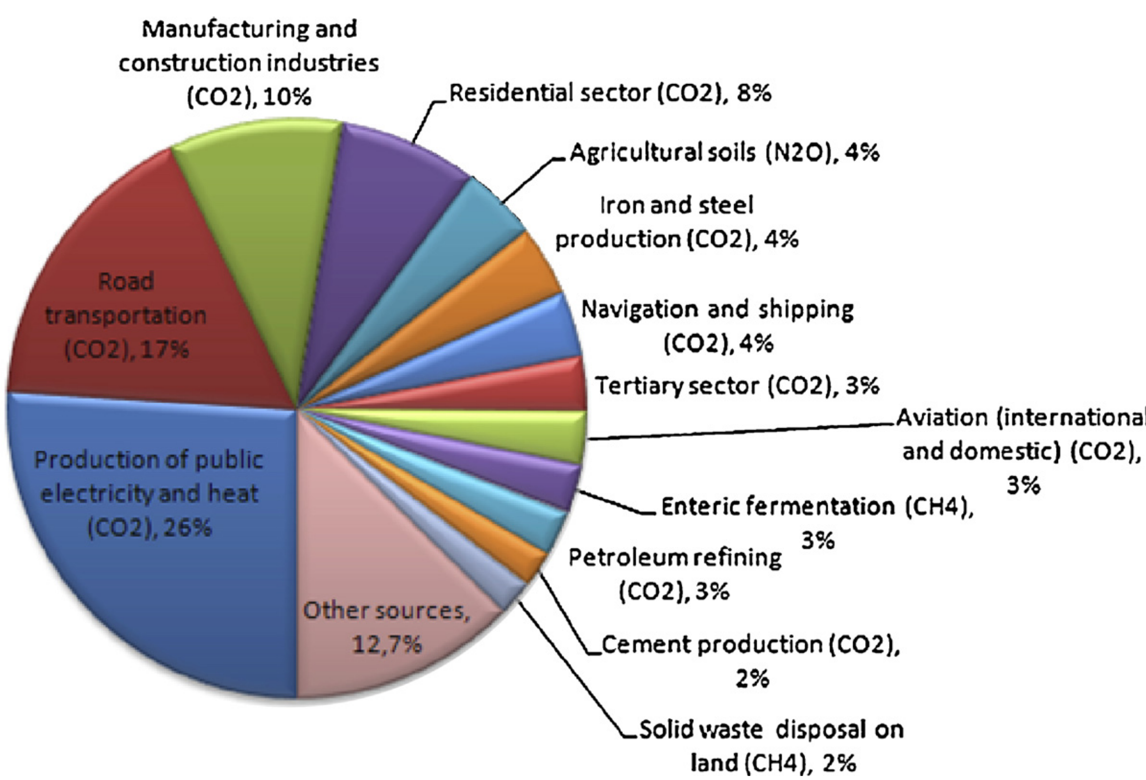

Fig. 1. Generation of carbon dioxide. *Data*: EEA.

Table 1
Efficiency improvements in T&D systems.

Cables	Superconductors, HVDC lines
Power flow control	Flexible AC Transmission System devices (FACTS)
	Phase Shifting Transformers (PST)
Transformers	High energy efficiency classes
	Amorphous Metal Distribution Transformer (AMDT)

Commission published an initiative to develop an energy policy for the EU introducing an action plan [3] to achieve three objectives by 2020: 20% reduction in greenhouse gases emissions, 20% share of renewable energy and 20% improvement of energy efficiency. This action plan later became the 2009/28/EC Directive [1]. This Directive establishes the common framework for the promotion of energy from renewable sources among the EU member states. Among other important issues, the Directive sets mandatory national targets for the overall share of clean energy in final energy consumption. Another objective is energy efficiency, stated as following: *In order to reduce greenhouse gas emissions within the Community and reduce its dependence on energy imports, the development of energy from renewable sources should be closely linked to increased energy efficiency*.

It is worth underlining the importance of energy efficiency in power systems. The term efficiency is usually associated with how energy is consumed at the point of end use, but the concept of efficiency can also be applied to energy production and distribution. In fact, the transmission and distribution (T&D) system is in charge of bounding generation and consumption and as in any electrical system, losses are unavoidable, due the equipments that build the T&D system and that are not ideal machines. Average transmission and distribution losses is around 5–6% of total power demand and 60–70% [4] of the loss is estimated to be lost in distribution system.

In order to reduce these losses, technical improvements can be made to guarantee energy efficiency in T&D. Assuming that usually overhead electrical lines cannot be expanded because of environmental, policy or space problems, the aim is to satisfy the electrical demand with the least amount of losses, a demand that has been constantly increasing in the past years. Energy efficiency improvements can embrace a wide part of the T&D systems and just to cite few of them (Table 1):

These practical applications are only some examples that show how technology can help empowering energy efficiency. At the same time, the power system cannot be seen as a sum of equipments only. Beside the general problem of improving energy efficiency, energy markets have undergone important changes, moving from public monopolies to private deregulated scenarios. Also, the integration of distributed generation is a relative new issue that has to be taken into account considering planning and design of power systems.

These aspects, along with the need of energy efficiency improvement and also with the aware of technological progress in power systems devices, open new ways to approach the study of power systems and the improvement of their performances. Technical limits, such as voltage control or system security, and economical objectives create a complex mathematical system that cannot be solved with simple computation tools, therefore the need to use different solving methods.

3. Optimization techniques

Problems in power systems are very complex and a large data set is always associated. Even if an exact algorithm may be developed and applied to find an exact optimal solution of the problem, its resolution time or space complexity may be not acceptable in a simulation scenario. However, many problems can be solved using an approximate or partial solution, if the dimension and the complexity of the problem do not encourage the use of exact resolution techniques. Heuristic algorithms work with approximated solutions and the objective is to find the optimum among all possible solutions. The collection of all possible solutions for a given problem can be considered as a search space. Heuristic solutions represent a compromise between quality and speed, being the solution admissible within a reasonable simulation time. Several heuristic tools have evolved to facilitate solving optimization problems that were difficult or almost impossible to solve. These tools include evolutionary computation, simulated annealing, taboo search, particle swarm and others. These heuristic tools may also be combined among themselves and, employing as well traditional approaches such as statistical analysis, they are able to solve extremely challenging problems using a so-called hybrid technique. Developing solutions with these tools offer several advantages:

- Broad applicability to different problems
- Simplicity of the approach used by these methods
- Robust response to changing circumstances
- Flexibility of their use

Heuristics algorithms can be classified in two categories: Greedy algorithms and Search algorithms. Greedy algorithms build the solution in a progressive way, obtaining a sequence of locally optimal choices. They have a good computing efficiency but they do not guarantee the global optimum. In fact, at each stage of the algorithm, a decision is made considering that it appears to be good, without regard for future consequences. This means that the solution is suboptimal because there is no previous certainty that the chosen solution is the global optimum. These algorithms are employed when the best answer is not needed and an approximated answer fits the initial requirements. In case the goodness of the solution needs to be improved, other heuristic methods are more suitable to fulfill this objective as it will be presented later. Metaheuristic algorithms can be considered as an upgrade of heuristics, because they progress towards an optimum through the evaluation of an objective function, comparing the new result to the previous optimum. Metaheuristic algorithms are meant to be a general way to solve problems and they are usually inspired by nature. In the next sections a more complete overview of these algorithms is presented.

3.1. Search algorithms

The simplest of search algorithms is exhaustive search, an algorithm that tries all possible solutions from a predetermined set and picks the best one. Local search is a version of exhaustive search focused on a limited area of the whole search space. Local search can be organized in different ways, such as hill-climbing techniques. These algorithms replace current solution with the best of its neighbors if the value obtained considering one of the neighbors as possible solution is better than the current solution one.

Divide and conquer algorithms try to split a problem into smaller problems that are easier to solve. Solutions of the small problems must be combinable to a solution for the original one. This technique is effective but its use is limited because there are not so many problems that can be easily split and combined in this way.

Branch-and-bound technique is a critical enumeration of the search space. This algorithm enumerates, but constantly tries to rule out parts of the search space that cannot contain the best solution.

Dynamic programming is an exhaustive search that avoids re-computation by storing the solutions of subproblems. The key point for using this technique is formulating the solution process as a recursion.

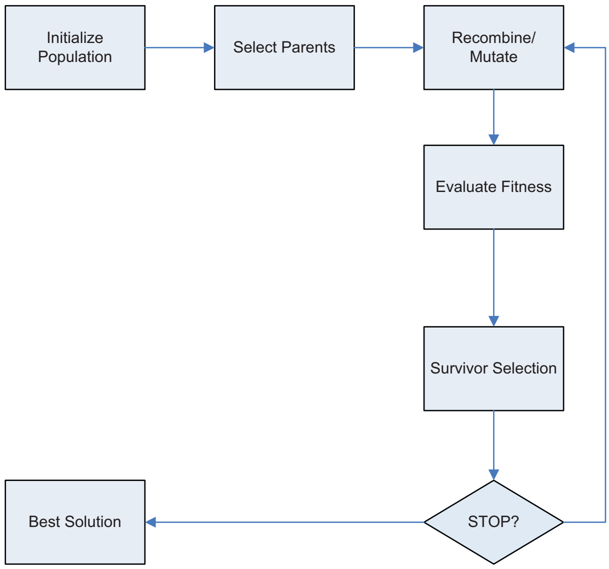

Fig. 2. Evolutionary algorithms.

A popular method to construct successively space of solutions is greedy technique, that is based on the evident principle of taking the (local) best choice at each stage of the algorithm in order to find the global optimum of some objective function.

3.2. *Evolutionary algorithms*

Evolutionary algorithms (EA) are methods that exploit ideas of biological evolution, such as reproduction, mutation and recombination, in order to find the solution. EA refer to a biological environment, applying the principle of survival on a set of potential solutions to produce gradual approximations to the optimum. They consider the idea of evolution as a consequence of reproduction, mutation and crossover. A new set of approximations is created by selecting individuals according to their objective function, which is called fitness function for evolutionary algorithms, and breeding them together using operators inspired from genetic processes. This process leads to the evolution of populations of individuals that are better suited to their environment than their ancestors. The main loop of evolutionary algorithms includes the following steps:

1. Initialize and evaluate the initial population.
2. Perform competitive selection.
3. Apply genetic operators (recombination and/or mutation) to generate new solutions.
4. Evaluate solutions in the population.
5. Start again from point 2 and repeat until some convergence criteria is satisfied.

Fig. 2 represents the flow chart of the process behind EA. In this figure, a population of candidate solutions is initialized considering random samples from the space of possible solutions. A new space solution is created by selecting the first pairs of parents and after this step they undergo genetic operators in order to obtain an offspring that will be evaluated with the fitness function. After these steps, the selection of survivors that will create the new offspring takes place and the process iterates until a certain desired stop criterion is reached.

Evolutionary techniques can differ one from another in the details of implementation and the problems to which they are applied. Their main common traits are based in the survival set of potential solutions and the evaluation of the goodness of a certain objective function. The fitness function defines the improvement of the algorithm. This means that the fitness function is responsible of assigning quality measures, therefore it is the evaluation point of the process.

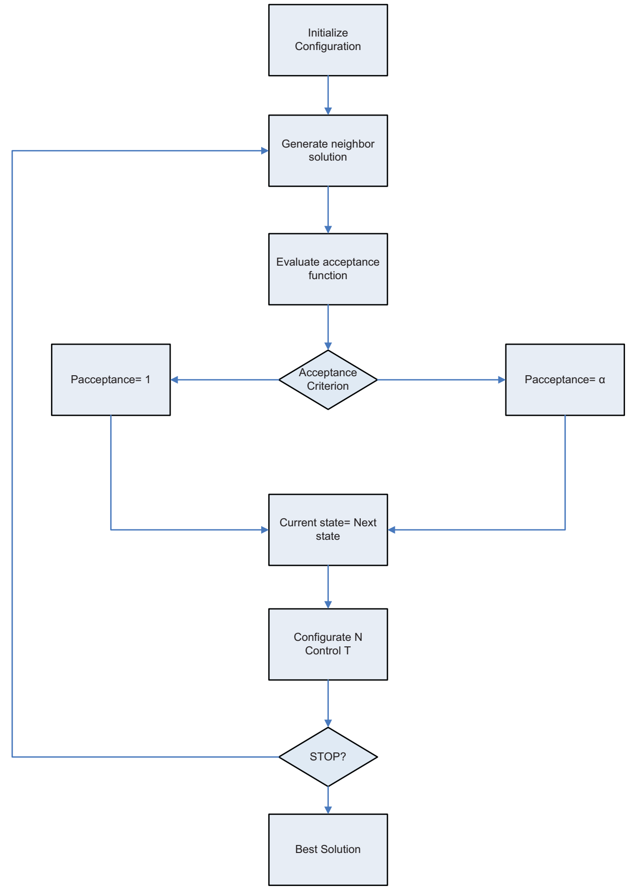

Fig. 3. Simulated annealing.

3.3. *Simulated annealing*

In statistical mechanics, a physical process called annealing is often performed in order to relax the system to a state with a minimum free energy. Based on the annealing process, simulated annealing (SA) was introduced for solving complicated combinatorial optimization. The name is taken from the analogy with the physical process of solids: the cost function and the solution in the optimization process correspond to the energy function and the state of statistical physics, respectively. In a large combinatorial optimization problem, an appropriate perturbation mechanism, cost function, solution space, and cooling schedule are required in order to find an optimal solution with simulated annealing. The algorithm used in SA presents an approach similar to hill-climbing, but occasionally it accepts solutions that are worse than the current one. The probability of such acceptance decreases with time. The cost function with a smoothing strategy enables SA to escape more easily from local minima and to reach rapidly the proximity to an optimal solution. This whole process is presented in Fig. 3, where the diagram blocks represent the main steps of the algorithm.

The beginning is a finite, large set of configurations, with an associated cost for each configuration. The solution is obtained by searching in the configuration space, the pair (configuration, cost) that offers the lowest value. At a certain temperature T, a sequence of N configurations is generated. A candidate configu-

ration is accepted if its cost is less than the current configuration one; the acceptance probability, $P_{acceptance}$, is then set to 1. However, if the cost is higher it can still be accepted but the acceptance probability is set

$$P_{acceptance} = \exp\left(\frac{f(S_i) - f(S_j)}{T_k}\right)$$

where S_i and S_j are respectively current and next state and T_k is the temperature. By applying this acceptance probability the algorithm is performing an uphill move and this allows to escape local minima. This is an important characteristic of this algorithm, since SA mainly deals with large data dimensions.

3.4. Taboo search

Taboo search (TS) is basically a gradient-descent search with memory. The memory stores a number of previously visited states along with a number of states that might be considered unwanted. This information is placed in a taboo list. The definition of a state, the area around it and the length of the taboo list are important design parameters. In addition to these taboo parameters, two extra parameters are often used: Aspiration and Diversification. All the neighboring states of the current state may also be included in the taboo list and this is an obstacle to optimization. In order to overcome this, aspiration is used and this means the selection of a new state; moreover diversification adds randomness to this search. If the TS is not converging, the search is reset randomly using diversification and to avoid local optima, the repetition of recently made moves is not allowed. The process is represented in Fig. 4 where its main steps are represented in the flow chart.

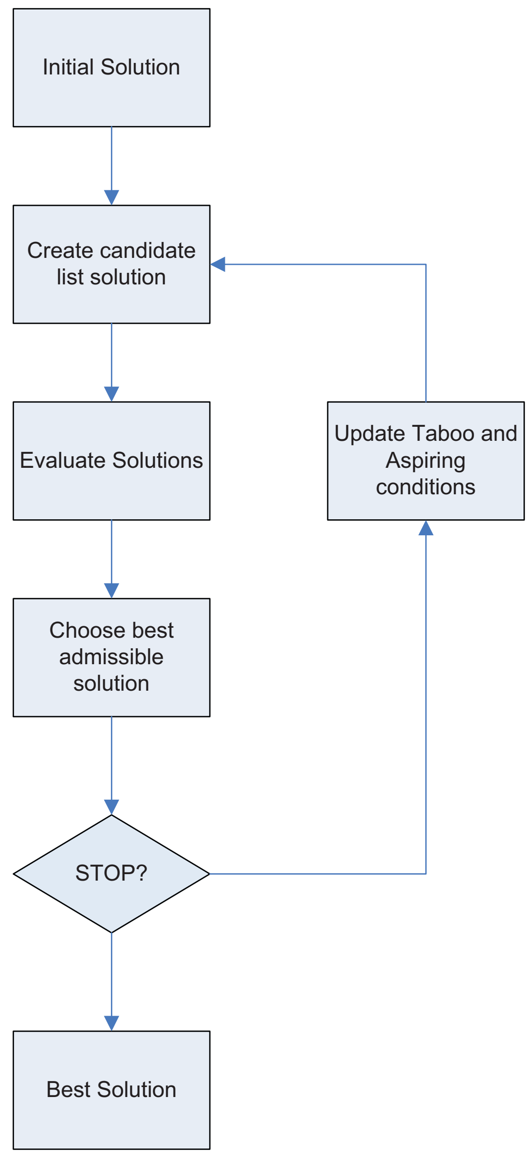

Fig. 4. Taboo search.

3.5. Ant colony optimization

Swarm intelligence is an artificial intelligence technique based on the study of the behavior of collective self-organized systems. Swarm intelligence applied to power systems includes ant colonies optimization (ACO), where artificial ants build solutions by moving on the problem graph and changing it so that future ants are capable of building better solutions. Artificial ants cooperate to find the solution to a combinatorial optimization problem by exchanging information via pheromone deposited on artificial paths. These considerations were made by studying food search behavior of real ants. The main advantages of ACO are:

- No premature convergence
- Rapid discovery of good solutions
- Find acceptable solutions in the early stage of the process

Fig. 5 represents the ACO algorithm and how it works.

This algorithm counts on discrete time steps and memory allocation of the positions occupied by artificial ants. Solution quality is evaluated through artificial ants trails and the shortest route determines the best solution that can be achieved employing this algorithm.

3.6. Particle swarm optimization

Particle swarm optimization (PSO) is based on the analogy of birds flocks and fish schooling and it deals with problems in which a best solution can be represented as a point or surface in an n-dimensional space. PSO presents a system that is initialized with a population of random solutions. Unlike other algorithms, however, to each potential solution (called a particle) is also assigned a random velocity and then it is flown through the problem hyperspace. Each individual exchanges previous experiences because of the human characteristic that is used in PSO algorithms is the concept of individual learning and information transfer. PSO has been found to be extremely effective in solving a wide range of engineering problems, since it can handle both discrete and continuous variables. It is very simple to implement and it solves problems in a short simulation time. The representation of the PSO process is presented in Fig. 6. After initialization of position and velocity with random values, each particle's position is evaluated in order to establish its fitness. This is the first step of the first loop in the algorithm, in which the position fitness is evaluated and if its value is better than the so far best value, it is set as new best position, p_{best}. Once all particles fitness are evaluated, the algorithm moves to the second loop, in which among all p_{best}, the best value obtained so far by any particle in the neighborhood of p_{best} is called g_{best}. The basic concept that lies behind PSO is to accelerate each particle towards its p_{best} and g_{best} locations.

The main advantage of swarm intelligence techniques is that they are impressively resistant to the local optima problem.

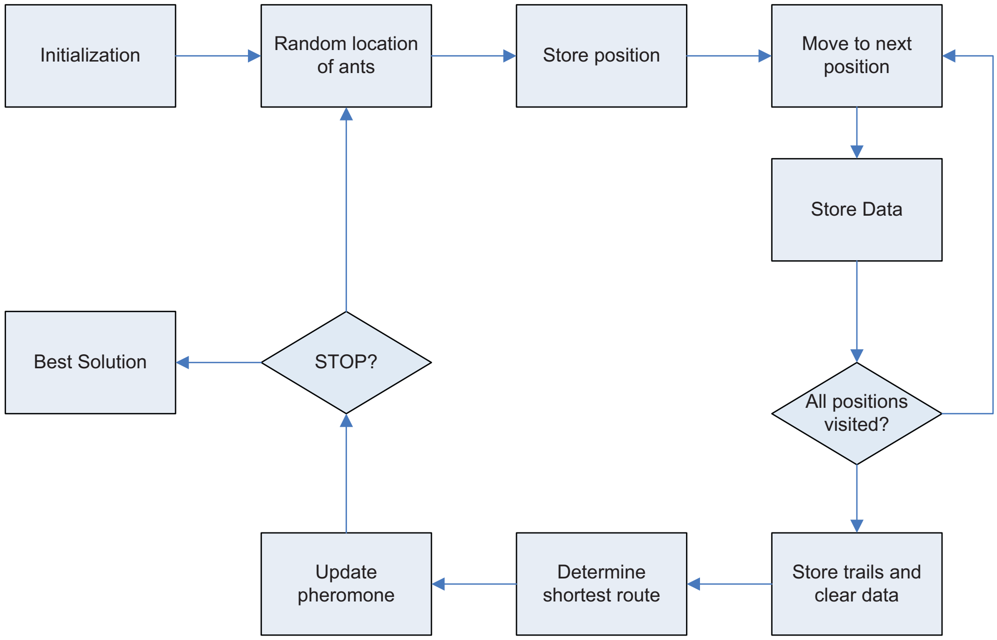

Fig. 5. Ant colony optimization.

3.7. Genetic algorithms

Genetic algorithm (GA) is a search algorithm based on natural selection and genetics; in fact, the role of mutation improves the individual quite seldom and therefore they rely mostly on applying recombination operators. The solution search is built in form of number strings, usually binary. The features of GA are different from other search techniques in several aspects. First of all, the algorithm is a multi-path algorithm that searches peaks in parallel and this reduces the possibility of local minima trapping. GA works with a coding of parameters instead of the parameters themselves. The coding of a parameter will help the genetic operator to evolve the current state to the next state with minimum computations. GA also evaluates the fitness of each string to guide its search instead of the optimization function. The algorithm flow chart is presented in Fig. 7.

The genetic algorithm only needs to evaluate objective function (fitness) to guide its search. There is no need for computation of derivatives or other auxiliary functions.

3.8. Evolution strategies and evolutionary programming

The evolution strategies (ES) technique employs real-coded variables and, in its original form, it relied on mutation as the search operator, and a population size of one unit. Since then, it has evolved to share many features with GA. The major similarity between these two types of algorithms is that they both maintain potential solution population and they use a selection mechanism for choosing the best individuals from the population. The main differences between ES and GA are (Table 2):

Evolutionary programming (EP) is a stochastic optimization strategy similar to GA, which emphasizes the behavioral link

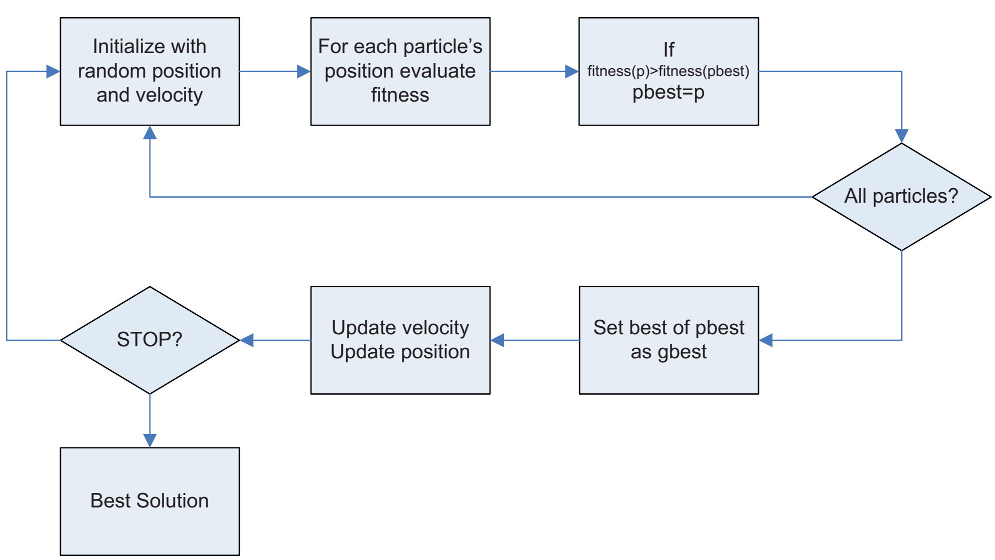

Fig. 6. Particle swarm optimization.

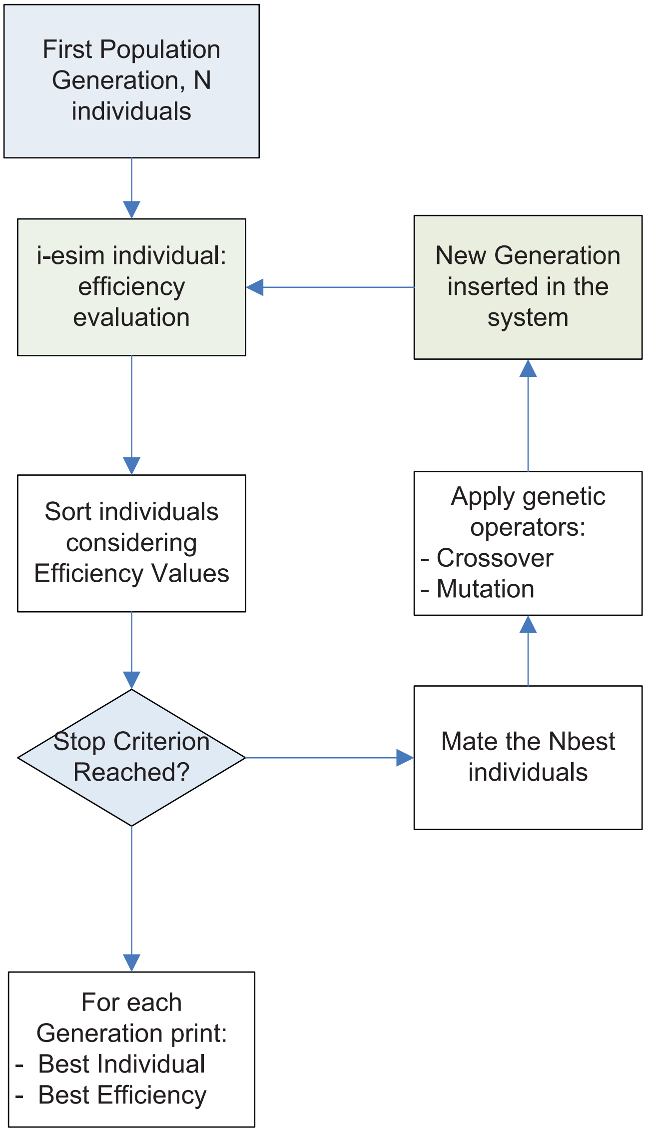

Fig. 7. Genetic algorithm.

between parents and their offspring, rather than seeking to emulate specific genetic operators as observed in nature. EP is similar to evolutionary strategies, although the two approaches developed independently. Like both ES and GA, EP is a useful optimization method when other techniques such as gradient descent or direct analytical discovery are not likely to be employed.

3.9. *Artificial Neural Network*

Artificial Neural Networks (ANN) are inspired by biological neuron systems. Although this is not a specific technique, being included in data mining theory, its applicability to power systems problems is worth to be mentioned. Thanks to ANN, helpful models can be ruled out in order to solve a wide range of problems.

Table 2
Differences between ES and GA.

ES	Operation on floating point vectors Use of mutation as the dominant operator Abstraction of evolution at an individual behavior level
GA	Operation on binary strings Relies mainly on recombination to explore the search space Maintains the genetic link

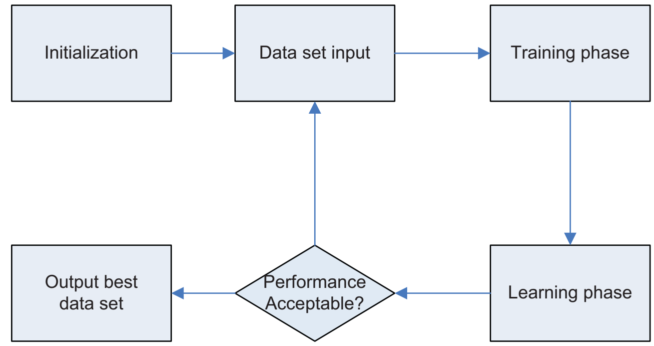

Fig. 8. Artificial Neural Networks.

ANN consist of units, called neurons, and interconnections among them. After special trainings on some given data set, ANN can make predictions for cases that are not in their training set, due to its pattern classification capability. Once trained ANN provides extremely fast solutions and by generalizing training data it can accommodate new patterns or new operating conditions. A simple model of how the algorithm works is presented in Fig. 8. Input/output data are fundamental in ANN because they convey the necessary information to discover the optimal operation point. A target response to input data is set as the error information that must be fed back to the system so that system parameters can be adjusted. This process is repeated until the performance is considered acceptable.

ANN may not always work well because it may suffer from problems of underfitting and overfitting. These problems are related to the accuracy of prediction. In fact, if a network is not complex enough there may be a simplifications of the rules to which the data obey, and this is called underfitting. On the other hand, the case of overfitting happens if a network is too complex; therefore the network may face the increase of the probability of considering the noise that usually exists in training data set and this may infer with the process. The quality of prediction after training is deteriorated in both cases. The problem of premature convergence is also critical for ANN and another low point of this algorithm is that given data may not cover a significant portion of the operating conditions.

3.10. *Application cases*

The previous section presented some of the most employed optimization techniques that can be applied to power systems. Some applications are here presented and a more extended bibliography is presented in Table 3. Herby a brief presentation of some selected problems solved by applying the aforementioned optimization techniques. Evolutionary programming applied to power systems presents power flow optimization [5,6] and reactive power dispatch as studied in [7,8]. All the qualities encountered for ANN, such as the simplicity of its application to different problems, make the approach especially suitable for system restoration and reconfiguration [9–11], faults detection [12] and power forecasting [13]. Application of ANN to renewable energy systems applications can be found in [14].

Another technique widely employed is genetic algorithm, whose applications are optimizing [15,16], planning reactive power [17,18], evaluating system losses [19] and also finding the optimal location of FACTS devices [20]. GA is very useful because it has robustness in finding an optimal solution and it can provide a near optimal solution in short simulation time. Applications of taboo search are useful for complex problems and in power systems TS has been applied to the unit commitment problem [21] and its hybrid version is presented in [22]. Considering the problem of transmission network expansion planning, solutions found using

Table 3
Topic related articles.

Author	Year	Issue	Method	Ref.
Zhe et al.	2009	Q optimization	ACO	[47]
Jalilian and Ziari	2008	OPF	ACO	[48]
Zhang et al.	2008	Q optimization	ACO	[49]
Abbasy and Hosseini	2007	Q dispatch	ACO	[50]
Mustafar et al.	2007	VC and Loss Min	ACO	[28]
Gardel et al.	2006	Multiob Q Comp	ACO	[29]
Kalil et al.	2006	Max Load in VC	ACO	[30]
Vlachogiannis and Lee	2005	Optimization	ACO	[51]
Ahuja and Pahwa	2005	Loss min in DN	ACO	[31]
Chin and Su	2005	PS Restoration	ACO	[52]
Gomez et al.	2004	Plan prim D circuits	ACO	[32]
Hou et al.	2002	ED	ACO	[53]
Jaipradidtham	2006	LDF	ANF	[54]
Wang et al.	2007	Theo ELC of DN	ANN	[55]
Flauzino et al.	2006	HI Faults in DS	ANN	[56]
Kang et al.	2006	LA of Taipower DN	ANN	[57]
Thukaram et al.	2005	Faults in radial DS	ANN	[58]
Uspensky and Kyzrodev	2005	DN reconfig for PSR	ANN	[9]
Islam et al.	2004	Transf tap changing	ANN	[59]
Khorashadi-Zadeh	2004	Detection HI faults	ANN	[12]
Fidalgo and Lopes	2003	Forecasting P Q	ANN	[13]
Sharma and Sreedhar	2003	Operation of DS	ANN	[60]
Bakirtzis et al.	1996	LF Greek PS	ANN	[61]
Gu and Rizy	1996	Control of CB and VR	ANN	[62]
Hegazy et al.	1994	Harmonic V in DS	ANN	[63]
Park et al.	1991	ELF	ANN	[64]
Chiang and Jean-Jumeau	1990	Network reconfig	ANN	[10]
Ebron et al.	1990	Detection of faults	ANN	[65]
Jeyakumar et al.	2007	Combined EED	EP	[66]
Contreras-Hernandez and Cedeno-Maldonado	2006	PS State Estimation	EP	[67]
Xu et al.	2006	EP State of the Art	EP	[68]
Sinha et al.	2003	ELD	EP	[69]
Ceciliano and Nieva	1999	Transm planning	EP	[8]
Yuryevich and Wong	1999	Optimal Power Flow	EP	[5]
Shi et al.	1998	Optimal power flow	EP	[6]
Wu and Ma	1995	Q dispatch	EP	[7]
Wei	2004	Comparison GA and EP	EP/GA	[70]
Li et al.	2009	Power Grid Opt	GA	[71]
Baghaee et al.	2008	Losses min	GA	[44]
Mahdad et al.	2008	FACTS, OPF	GA	[72]
Kumar et al.	2008	Service Restoration	GA	[73]
Zaho et al.	2006	Opt of ES OWF	GA	[16]
Samaan and Singh	2005	Reliability PS	GA	[74]
Gerbex et al.	2001	Opt location FACTS	GA	[20]
Zhang et al.	1998	Q optimization	GA	[15]
Fukuyama and Chiang	1996	Gen expansion	GA	[18]
Lee et al.	1995	Q planning	GA	[75]
Miranda et al.	1994	Network planning	GA	[17]
Sundhararajan and Pahwa	1994	Selection of C	GA	[76]
Mishra et al.	2007	Transm loss red	GA	[19]
Gopalakrishnan et al.	2004	Q planning	HEP	[77]
Tuppadung and Kurutach	2006	Phase Balancing	mPSO	[36]
Martins et al.	2003	PS fault location	ANNE	[78]
Chow et al.	1993	Distri fault causes	ANNF	[79]
Lesani and Pouya	2009	Q management	PSO	[39]
Zaraki and Bin Othman	2009	Load Dispatch	PSO	[40]
Li et al.	2008	Loading Opt	PSO	[80]
AlRashidi and El-Hawary	2006	ED with EC	PSO	[37]
Heo et al.	2006	Multi control plants	PSO	[81]
Vlachogiannis and Lee	2006	Opt Steady-State PS	PSO	[34]
Abido	2002	OPF	PSO	[33]
Yoshida et al.	2000	Q VC	PSO	[35]
Gaing and Gaing	2003	ED	PSOGA	[38]
Mantawy et al.	1998	Unit Commitment	TS	[21]
Mantawy et al.	1999	Integrate UC	TS	[22]
Gallego et al.	1998	Planning	TS	[23]
Gallego et al.	2000	Planning	TS	[24]
Gerbex et al.	2003	FACTS location	SA	[26]
Gallego et al.	1997	Planning	SA	[25]
Romero et al.	1996	Planning	SA	[27]

the TS approach are studied in [23] and [24]. Simulated annealing is also employed for planning [25] and for FACTS location [26]. SA is effective in network reconfiguration problems for large-scale distribution systems and its search capability becomes more significant as the system size increases; studies in this area are presented in [25] and [27]. Comparing these last 3 methods, GA and TS are faster methods if searching for the optimal location of a FACTS device, for instance.

Considering now swarm optimization, ant colony optimization and particle swarm optimization are also useful to solve different types of problems. Despite being a relatively new method, ACO is very well employed in routing and logistic problems but it can be also used in power systems where complex combinatorial optimization problems must be solved. The application of ACO algorithms to power systems leads to the solution of problems such as voltage control [28], reactive power compensation [29], maximum loadabilty [30], losses minimization [31] and system planning [32]. This technique is also employed to solve issues as load flow optimization [33,34], reactive power control and planning [35], phase balancing [36] and economic dispatch [37,38]. PSO is also applied to reactive management [39] and load dispatch [40]. In [41] a wide review of economic dispatch (ED) resolution by means of PSO is presented. Here PSO perfectly fits to this non-linear non-convex type objective function, whose equality and inequality constraints are intense. Modifications to the PSO formulation and its application to ED are also proposed.

A good example of application of several optimization techniques to the same problem, sizing photovoltaic systems, is presented in [42]. The topic of the article is not the same as this review aims to present, but it is however important to show how many applications of optimization techniques there can be. In [43] multi-objective optimization is analyzed to solve the planning of distributed energy resources: several problems are presented along with the formulation of multi-objective optimization.

Table 3 present a longer collection of articles than those presented in the previous sections.

4. Problems resolution by means of optimization techniques

Several kinds of optimization techniques are presented in Section 3, while in this new section some problems solved with these techniques are presented, considering the application of different heuristic methods.

4.1. Optimal power flow

Optimal power flow (OPF) is an optimization problem in the power system area and the output of the OPF analysis are control settings of the systems. In fact, power system operators need to determine the state that combines the lowest operational cost with security and OPF allows determining the most efficient, low cost and reliable operation of a power system by dispatching the available electricity generation to supply the load. This is a non-lineal constrained optimization problem and its mathematical formulation is the following consists in minimizing an objective function restricted by equality and inequality constraints as presented below.

$$\begin{aligned} &\min\ J(x,u)\\ &f_{eq}(x,u)=0\\ &f_{op}(x,u)\leq 0\\ &f_{cv}(x,u)\leq 0 \end{aligned}$$

J is the objective function, f are the constraints of the problem, x is the vector of the state variables and u is the vector of the control variables.

The most common objective functions are usually:

- Operation cost minimization
- Losses minimization
- Secure operation, minimum deviation of control settings
- Minimize or maximize power transfer
- Power flow control devices settings

Considering the constraints of the objective function, they are of three types: equality, operation and control variables constraints. In detail,

$$f_{eq}=0$$

This constraint represents conventional power flow equations such as Kirchoff laws and network components.

$$f_{op}(x,u)\leq 0$$

This equation represents the operation constraints that the system has to respect. Usually these constraints are:

- Voltage at load buses
- Reactive power of PV generators
- Branch currents, MW, MVAr and MVA amount
- δ and V drop

$$f_{cv}(x,u)\leq 0$$

The variable system control constraints usually represent:

- Tap positions of installed transformers
- Active power generators
- MW interchange transactions
- Shunt reactors/capacitors

This system has to be solved, optimizing the objective function J and respecting of the constraints. To approach this complex problem heuristics method can be applied.

4.1.1. Particle swarm optimization

As previously mentioned, the goal of OPF is to find the optimal settings of the control variables, in order to minimize the objective function. Abido [33] introduced particle swarm optimization to solve the OPF problem because this is a highly non-linear and multimodal optimization problem. There may be one of more local optima and some properties of the problem do not meet the conditions used to verify that a point is a minimum or maximum point. Heuristics methods are useful with non-convex problems, non-smooth and non-differentiable. Also, other devices installed in the power system may increase the difficulty to treat this optimization problem with conventional optimization methods, such as the non-linear behavior of FACTS devices or the valve point loading of thermal generation.

The theory behind PSO has been already explained in Section 3.6 and here its application is presented. PSO is employed mostly because it is simple in concept, it is easy to implement, it is efficient and it is a flexible mechanism to enhance global and local exploration abilities. Abido presents the application of PSO to different objective functions, in the IEEE 30-bus test system:

- Minimization of fuel cost
- Voltage profile improvement
- Power system voltage stability

Considering the minimization of fuel cost, the research led by Abido shows an improvement of the optimal point of a 11.25%.

Table 4
Parameters for ACO optimization.

x	Control variable
x_{max}	Maximum x
d	Distance for every ant tour
d_{max}	Maximum d

Similar good results are also found for the other two objective functions.

4.1.2. Evolutionary programming

As previously mentioned, evolutionary programming (EP) is a stochastic optimization method that works evolving a population of candidate solutions towards the global minimum or maximum. EP is a very suitable method when many local optima exist and the algorithm is not sensitive to starting points. In his work, Yuryevich and Wong [5] applies EP to the IEEE 30-bus test system in order to find the best solution for the OPF problem. Here the optimality is measured by a fitness function defined as

$$f_i = \frac{M}{C_i + \sum_j VP_j + SQ}$$

The fitness function is built considering M as the maximum possible cost for generation, C_i the generation cost of individual i, VP_i and SQ penalties terms for violating voltage limits and slack limits.

With a competition-tournament scheme, the best fitted individuals are selected to build a new population. Three cost curves are taken into account to study the effectiveness of the proposed method. The first curve is a quadratic cost curve and the results show an average cost of $803.51, with a minimum of $802.62 and a maximum of $803.51. This result, compared to the one obtained with a steepest descent (SD) method, does not top the $802.4 of the SD method, however it does not violate the slack limits as the SD does. The second curve is a picewise quadratic curve, and using the EP method the results are better than the ones obtained with the SD method. In fact, the solution of the SD method is $850 while the average solution obtained with the EP method is $649.67, with a minimum of $647.779 and a maximum of $652.67. The last curve analyzed is a sine component and its characteristic is to give a solution that is not so strongly dependent on the starting point, as it is for the SD method.

4.2. Losses minimization

Transmission losses are very important to be considered in case of long distance transmission and low load density over a vast area. Losses can arise from lines and cables, transformers and machines. Their amount is between 20% and 30% of total generation and this is a huge problem to be solved, since they increase the operating cost of running a power system. Moreover, thermal losses reduce the overall lifetime of the electrical equipments. Losses can be mitgated by several means and applying different techniques (Table 4).

4.2.1. Ant colony optimization

Ant colony optimization (ACO) can be applied to several problems because of its easy implementation, its flexibility and the fact that it can escape local optima given by a certain problem. Mustafar et al. [28] presents an application of ACO to losses reduction using transformer tap settings to control reactive power. The final objective is to minimize losses optimizing tap settings. The study test system is the IEEE 30 bus test system and the problem presents T_i, $i \in (1,4)$, as variables representing transformers tap ratios and the constraints are given by the voltage set. The fitness function is here represented by

$$x = \frac{d}{d_{max}} x_{max}$$

Being

The ACO algorithm here presented works in the following way:

1. Initialization
   Control parameters are chosen.
2. First node generation
3. State transition rule
   The ant decides which node has to be visited next, calculating next node s and the probability to choose node s after node r.
4. Local updating rule
   The amount of pheromones is updated and the already visited paths become less desirable.
5. Fitness evaluation
   The control variable is updated.
6. Global updating rule
   The amount of pheromones generated by the ant with the shortest tour is updated.
7. End condition
   The maximum number of iteration is reached and the best path is recorded.

The results show that losses are reduced around a 4% only at high loading conditions while the voltage profile is always increased. The number of ants used to simulate the system does not influence the results.

4.2.2. Genetic algorithm

Losses reduction can be achieved installing devices that can directly modify the T&D network. An example are FACTS devices, that have multiple applications and they can control several electrical values. To empower their use, an optimal location is a good starting point. To do so, the genetic algorithm (GA) is a good solution as presented in [44], where an IEEE 30 bus test system is employed to study this problem (Table 5).

Table 5
GA parameters.

a_1, a_2, a_3	Coefficients optimized by trial and error
L_{ij}	Voltage stability index between bus i and j
Losses	Total system losses

Here a voltage stability index is defined and the fitness function is formulated as it follows:

$$Fitness = a_1 \cdot \max(L_{ij}) + a_2 \cdot (TotalInvestmentCost) + a_3 \cdot (Losses)$$

Being

Simulations are performed considering different scenarios, depending on the FACTS device type. The results show an average improvement of 5% in losses reduction and similar results are obtained for voltage profile.

4.3. Reactive power management

Reactive power management deals with several issues, mainly: voltage quality improvement, network losses reduction and system security. The constraints to this problem are usually limits on bus voltages, tap settings and the location of reactive power compensation. All summed up, it becomes a multi variables, multi constraints and non-linear problem that can be solved employing different approaches.

4.3.1. Evolutionary programming

A possible technique applied to solve the reactive power management problem is evolutionary programming (EP), as presented in [7]. The proposed EP method has been evaluated on the IEEE 30-bus system and simulation results, compared with those obtained using a conventional gradient-based optimization method. A pop-

ulation of solutions is maintained at each iteration and these solutions propagate into future generations probabilistically, as function of their overall merit. The population can move over hills and across valleys, therefore global optimal point can be discovered. The objective is to minimize losses and the objective function is defined as

$$\min f_Q = P_s(V,\delta) + \sum_{i \in V_{\lim}} \lambda_i (V_i - V_{\mathrm{i}\lim})^2 + \sum_{i \in Q_{\lim}} \lambda_i (Q_{Gi} - Q_{\mathrm{Gilim}})^2$$

EP does not need to differentiate the objective function and constraints but it uses probability transition rules to select individuals in a population to reproduce new generations. An individual competes with some other individuals in the old generation and the mutated old generation. Winners with the same number as the individuals in the old generation form the next generation. The EP is carried out mainly with three operations: mutation, competition and reproduction.

The control variables of the transmission network are arranged as elements of an individual in populations during evolutionary search. The results show an increase in power savings of an 8% compared to those obtained with gradient methods. The EP method is able to undertake global search with a fast convergence rate and a feature of robust computation, and possesses an inherent capability for parallel processing.

4.3.2. Artificial Neural Network

A good tool to improve reactive power management is power forecasting. Quality prediction of load evolution at different levels of distribution networks is a basic requirement for an adequate operation planning of modern power system. As discussed in [13], based on historical data, an algorithm using the Artificial Neural Network (ANN) method can define good quality estimations of future values. ANN offers several advantages:

- No system model required
- Bizarre patterns toleration
- High adaptative capacity

The forecasting tool presented provides active and reactive power at primary substation's transformers and current intensity at primary substation feeder. The tool is not here presented and how ANN works has been already explained in Section 3.9, nevertheless it is important to present a valuable application of this technique.

4.4. Detailed problem resolution example: FACTS location using genetic algorithm to increase energy efficiency in distribution networks

This section presents the work developed in [45] about how genetic algorithm (GA) can be applied to find the best location and configuration for FACTS devices in a distribution network. In fact, the application of FACTS devices employing a GA optimization technique, can actually improve energy efficiency in power systems. GA will be applied so that the location of FACTS devices and the reactive power considered are optimal. Here GA is applied to a power system of N_{bus} nodes to maximize energy efficiency (η). For each individual i out of the possible N, an array carries the values that represent the i-th individual: the node, N_{node}, the FACTS device reactive power Q_{facts} and the efficiency of the system η_i. Two different MATLAB*R* programs are applied to the distribution network:

- A power flow program to evaluate the network's efficiency
- A GA based program to optimize FACTS location and therefore improve energy efficiency

These programs are meant to evaluate the evolution of network efficiency through the number of generations along with the best node/best reactive power evolution. The process sorts out individuals of the population considering their efficiency values and it evaluates the stop criterion set for the problem. Later on, the algorithm applies the GA rules that are necessary to grow the population and in the final phase the algorithm outputs the best values reached for each generation.

4.4.1. Methodology

4.4.1.1. Objective function and constraints. In this paper the objective function is the efficiency (η) of the network. The final aim is to maximize η by placing the FACTS device in a suitable place and with the best Q output.

The evaluation of the fitness of the objective function for each individual is preformed through the power flow program created by the authors and the result of the load flow calculation is used to check voltage drop constraints for the network under study. Therefore the maximization of the objective function does not have explicit and external constraints, as for instance a line loadability would be; there are however implicit constraints that must be respected, otherwise the power flow calculation would stop, producing an error message.

4.4.1.2. Simulation tool. GA is applied to a power system of N_{bus} nodes to maximize energy efficiency (η) and a first population of N individuals is created to represent a set of possible solutions. For each individual i out of the possible N, an array carries the values that represent the i-th individual: the node, N_{node}, the FACTS device reactive power Q_{facts} and the efficiency η_i. The algorithm flow is represented in Fig. 9.

Block A. The first step is to initialize the first generation (A1) and then (A2) counters for both generation and individuals are set to: $N_{gen} = 1$ and $i = 1$ where i is the i-th individual of the generation.

Block B. The system undergoes a power flow calculation (B1) for each i individual. Next in line is the evaluation of η (B2) and the counter is increased to $i = i + 1$ (B4) while the individuals stop criterion is not reached (B3). The stop criterion is set to be the number of maximum generations considered along the process, N_{gen}. If the individuals counter has finished his cycle, then the generation counter is increased (B5). The process then sorts out individuals considering their η values (B6) and the generation stop criterion is evaluated (B7). If the stop criterion has not yet been reached, only the first N_{best} are mated (B8). Later on the same flow line, genetic operators are applied to the couples (B9), the new population is inserted again in the system (B10) and the loop is closed (B1). The stop criterion is then evaluated to define if the maximum number of generations has been reached or not (B7). After the mating couples are decided, genetic operators are applied in order to obtain new solutions. Genetic operators are mutation and crossover and the possibility for a node to inherit the DNA from father or mother node is set through the variable α that takes random values between 0 and 1. The new generation node will undergo mutation and crossover depending on the values of α. These new solutions are reintroduced in the system and again all individuals are evaluated through the fitness function.

Block C. The algorithm enters the final phase (C1) once the stop criterion has been reached and it outputs best node, best efficiency and reactive power value.

4.4.2. Simulation results

The algorithm is applied to a 33 bus radial distribution system using data presented in [46] and Fig. 10 represents a sketch of the network under study.

The simulation is set for a number of generation N_{gen} and the maximum number of best individuals is set to be N_{best}.

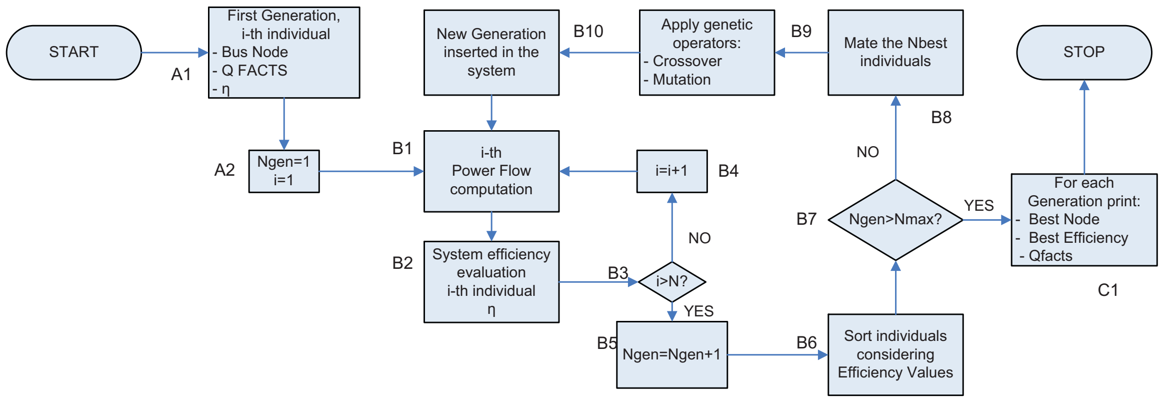

Fig. 9. Algorithm chartflow.

These individuals are the new genitors of the new population and in order to establish the individuals ranking, system efficiency is evaluated through the power flow program. For each new population the first 3 individuals with the best efficiency are chosen to reproduce and their behavior is implemented considering their probability of reproducing, including also crossover and mutation.

A first simulation is performed without the use of GA and no FACTS devices are placed on the network. The efficiency of the system is evaluated using the power flow program elaborated by the authors. The result of the efficiency calculation is $\eta = 0.9274$.

The next step is to add the possibility to locate a FACTS device in the network understudy. Economical issues are here not considered, since the main drive of the study is to enhance the efficiency of the system. Simulations are then performed considering the FACTS devices located at 6 different nodes, as the first set of possible solutions. The original FACTS devices location and reactive power are presented in Table 6.

Here the initialization of the population is considered to be totally random, given the medium dimension of the network. In case of studying a wider network, another initialization process would be used, taking into account for instance the saturation of certain branches.

Fig. 11 shows the evolution of the efficiency through the number of generations and also the evolution to the best node with its best reactive power input.

For this specific study the results obtained show which is the best node to be chosen in order to obtain an optimal location of FACTS devices. The best efficiency is obtained placing the FACTS device in the node indicated in Table 6 and Fig. 11 and this value, $\eta_{FACTS} = 0.9403$ improves the first value of η obtained running the power flow without GA, which was $\eta = 0.9274$. The results show how the efficiency varies considering different nodes as best candidates and that the final result not only gives the best efficiency score and the value of best Q, but it is also a quite stable result throughout the simulation time. Given reactive power value of FACTS device, in a rather simple and quick way it is possible to decide which nodes are the best suitable to place these kind of devices and therefore later perform an economical analysis if needed.

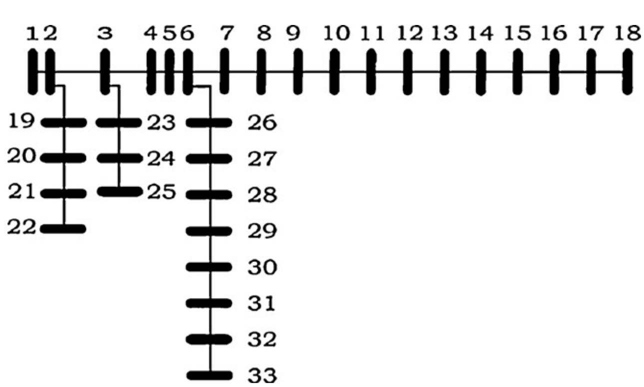

Fig. 10. 33 Bus distribution system.

Table 6
Initial population.

Node	Q
6	−0.5
3	−1
10	−0.45
20	−0.6
18	−0.9
5	1

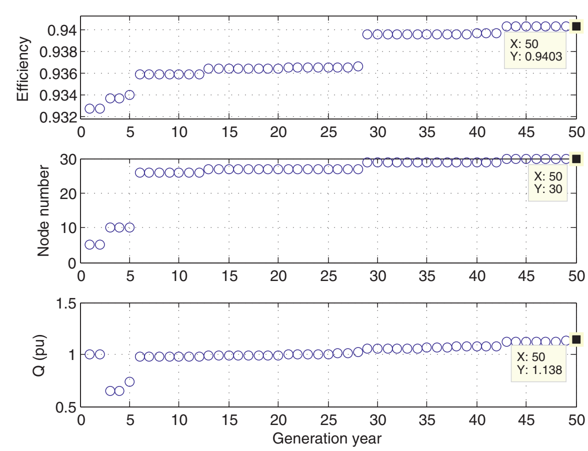

Fig. 11. Efficiency evolution.

5. Conclusions

In order to improve energy efficiency in power systems, both technology and policies can help to find the best performance of the system. Technology can nowadays offer a wide variety of different equipments with several efficiency options and the installation of these equipments can surely enhance the energy efficiency of the system from a pure *energy in–energy out* point of view. Moreover, policies are a good way to empower energy efficiency in power systems.

Considering transmission and distribution systems, there are several issues that must be faced in order to guarantee the best

energy efficiency:

- Losses minimization
- Reactive power management
- Load forecasting
- FACTS optimal location
- Optimal power flow

Many others are the problems that can be also encountered in T&D systems, but are slightly less significant to energy efficiency enhancement: voltage control, economic dispatch and others.

These problems are very complex and with dimensions that require the use of alternative techniques that can ensure a good, robust and above all quick solution. Heuristic and metaheuristic methods are indeed a good way to solve these problems and it is not deniable that if well used they can be a good tool to solve such complex problems. In fact the application of an adequate method is important, otherwise the performance will not be satisfactory.

The given overview proofs the wide use of optimization techniques in transmission and distribution systems and the benefits that their application can have on energy efficiency. Although optimization techniques alone are not the only good practice in power systems, in order to improve the performance of a system, they are a very good support when the complexity of the problem does not allow the use of exact optimization techniques.

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